Partitioning Composite Finite Systems

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Abstract

We compare different analytical and numerical methods for studying the partitions of a finite system into fragments. We propose a new numerical method of exploring the partition space by generating the Markov chains of partitions based on the Metropolis algorithm. The advantages of the new method for the problems where partitions are sampled with non-trivial weights are demonstrated.

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Many fields of physics deal with the common phenomenon that, under appropriate conditions, a compound system can disintegrate into constituents. Let us consider an isolated system composed of A_0 identical particles (we call them nucleons) which are kept together by some attractive forces. If sufficient energy is put into the system, it will disintegrate into fragments. These fragments can either be individual nucleons or bound clusters of several nucleons. Examples of such processes abound in condensed matter physics, nuclear physics, and astrophysics. In order to provide a microscopic description of such processes, one must sort out possible partitions of the system and compare their probabilities. At the first step, it is necessary to develop methods of generating and

sampling the partitions. The aim of this paper is to propose a new and efficient method of doing this.

The obvious way to proceed is simply to construct all partitions directly and calculate the characteristics of interest. Unfortunately, this approach is possible only for small A_0 because the total number of partitions, $P(A_0)$, grows rapidly with A_0. For instance, $P(100) = 190569292$ while $P(200) = 3972999029388$. Even if one needs only perform a few non-trivial operations for each partition, this task becomes intractable for $A_0 > 100$. We shall, however, reserve this direct method for checking the more practical methods presented below.

First, we address an analytical approach to dealing with the Euler's partitioning problem. It is based on the Generating Function (GF) formalism [1]. This approach can be applied successfully for calculating average characteristics of partitions. We characterize each partition f by the multiplicities $\{N_A\}$ of fragments with different nucleon numbers A, $1 \leq A \leq A_0$. Then, the conservation of the total nucleon number for each f is expressed as:

$$\sum_{A=1}^{A_0} N_A^{(f)} A = A_0 \ . \tag{1}$$

Evidently, the total fragment multiplicity M in the channel f is

$$M_f = \sum_{A=1}^{A_0} N_A^{(f)} \ . \tag{2}$$

Following a well-established method in mathematical literature [1], we introduce an unconstrained generating function $Z(x)$:

$$Z(x) = \sum_{N_A=0}^{\infty} \prod_{A=1}^{\infty} \left(c_A x^A\right)^{N_A} = \prod_{A=1}^{\infty} \frac{1}{1 - c_A x^A} \ , \tag{3}$$

where the c_A are arbitrary numbers which can later be taken as $c_A{=}1$. Here x can be considered as a Lagrange multiplier. Now we can calculate the total number of partitions, $P(A_0)$, by simply expanding eq.(3) and counting the coefficient of x^{A_0}. The results for large A_0 or $x \to 1$ are well approximated by famous Hardy-Ramanujan formula:

$$P(A_0) = \frac{1}{\sqrt{48 A_0}} \cdot \exp\left(\pi\sqrt{\frac{2A_0}{3}}\right) + O\left(\left[\exp\left(\pi\sqrt{\frac{2A_0}{3}}\right)\right]^{1/2}\right). \tag{4}$$

One can use this generating function to calculate approximately the average multiplicities of fragments $\langle N_A \rangle$ over all partitions. This is done by replacing the exact constraint of eq. (1) by an approximate one:

$$\sum_{A=1}^{\infty} \langle N_A \rangle A = A_0 \, , \tag{5}$$

i.e. the constraint is fulfilled on average only. Then one obtains

$$A_0 = x \frac{\partial \ln \left(Z(x) \right)}{\partial x} = \sum_{A=1}^{\infty} \frac{A x^A}{1 - x^A} \, , \tag{6}$$

where we have set the $c_A = 1$. This equation must be solved to determine x. A very good approximation to the solution at large A_0 is

$$x = \exp \left(-\pi \sqrt{\frac{1}{6A_0}} + \frac{1}{4A_0} \right) . \tag{7}$$

Now, the mean multiplicities of fragments can be calculated as:

$$\langle N_A \rangle = c_A \frac{\partial \ln \left(Z(x) \right)}{\partial c_A} = \frac{x^A}{1 - x^A}. \tag{8}$$

The result is shown in fig. 1 (top panel) in comparison with the results of the direct method in which all the partitions are included in the calculation. It is seen that the agreement is good except for a slight discrepancy at large A which indicates an expected finite size effect. Indeed, eq. (8) gives small but finite $\langle N_A \rangle$ even for $A > A_0$ when the exact calculation gives strictly zero. The average multiplicity of all fragments can be calculated as $\langle M \rangle = \sum_A \langle N_A \rangle$ and is well approximated by the expression

$$\langle M \rangle = \frac{1}{\pi} \sqrt{\frac{3A_0}{2}} \ln \left(\frac{6A_0}{b\pi^2} \right) , \tag{9}$$

with $b = 0.315087$. For example, for $A_0 = 100$ it gives us $\langle M \rangle = 21.32$ while the exact value obtained with the direct method is 21.75.

More generally, it is useful to consider the situation in which partitions are biased with certain weights. In statistical theory, for example, identical fragments are counted in a partition sum with a factorial weight $1/N_A!$. The weight of a partition is then $W_f = 1/\prod_A N_A!$. In this case, the corresponding generating function can be written as:

$$Z(x) = \sum_{N_A=0}^{\infty} \prod_{A=1}^{\infty} \frac{\left(c_A x^A \right)^{N_A}}{N_A!} = \prod_{A=1}^{\infty} \exp \left(c_A x^A \right) . \tag{10}$$

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This form is similar to the grand canonical partition sum if one identifies x with the fugacity and c_A's with the internal partition sums of individual fragments [2]. Now instead of eqs.(6) and (8) one easily obtains (after substituting $c_A=1$):

$$A_0 = \sum_{A=1}^{\infty} Ax^A, \quad \langle N_A \rangle = x^A \ . \tag{11}$$

For $A_0 \to \infty$ one finds the approximate expressions $x = \exp(-1/\sqrt{A_0})$ and $\langle M \rangle = \sqrt{A_0}$. These results are shown in fig. 1 (bottom panel). The mean multiplicity $\langle M \rangle = 10$ for the case $A_0 = 100$ is in good agreement with the exact value of 9.77 obtained by direct calculation.

For the two simple examples considered above one can calculate also the multiplicity distributions of individual fragments. It is clear from the structure of the generating functions, eqs. (3) and (10), that the distribution is exponential in the first case and Poissonian in the second case. The normalized multiplicity distributions are respectively,

$$P_1(N_A) = \frac{1}{1+\langle N_A \rangle} \left(\frac{\langle N_A \rangle}{1+\langle N_A \rangle} \right)^{N_A} \quad , \quad P_2(N_A) = \exp\left(-\langle N_A \rangle\right) \frac{\langle N_A \rangle^{N_A}}{N_A!}. \tag{12}$$

As seen in fig. 3, the exact results are reproduced by these distributions with high accuracy.

In practice, however, direct accounting for all partitions can only be done for $A_0 \lesssim 100$. If the weight factors are complicated, it can also be hard to find an analytical solution. Multiplicity distributions and correlations, which are of considerable physical interest, are particularly difficult to obtain[1]. There is thus a need for another method, presumably based on the generation of individual partitions. Obviously, it must be efficient enough to permit computer simulation within a reasonable time.

A first attempt to develop such a method was made in refs. [4] by introducing a bias function $b(A_0, M) = P(A_0, M)/P(A_0)$, where $P(A_0, M)$ is the total number of partitions with exactly M fragments. It can be calculated using the recursion relation [1, 4]

$$P(A_0, M) \ = \ P(A_0 - M, M) \ + \ P(A_0 - 1, M - 1) \ . \tag{13}$$

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[1]In this respect an interesting development of an analytical method was recently made in ref. [3].

As before, the total number of partitions is

$$P(A_0) = \sum_M P(A_0, M). \tag{14}$$

This bias function is used to generate a sample of partitions by the Monte Carlo method. First, M is selected randomly with a probability given by the bias function, $b(A_0, M)$. Then, a random partition with selected multiplicity is generated as described in ref. [2]. We shall refer to this method as Biased Random Generation (BRG). Another Monte Carlo method of generating partition samples using a bias function obtained with a Laplace transformation is described in ref. [5].

Figs. 1 and 2 (top panel) show how well the BRG method works in the case when all partitions have equal weighs. The results are presented for $A_0=100$ and summarize the outcome of 10^5 randomly generated partitions. By construction, this method is guaranteed to give the correct multiplicity distribution as shown in fig. 2 (top panel). It is less trivial that it reproduces correctly also the mean multiplicities of individual fragments as well as other distributions. Unfortunately, the BRG method has a serious drawback: It produces correct results only for the case in which the weights of partitions are equal. This is not surprising given that eq. (13) was obtained under this assumption. When we introduce nontrivial weight factors, for instance relative factorial weights $W = 1/\prod_A N_A!$ for partitions with fixed M, the method fails. This is clearly seen in the bottom panel of fig. 1 for mean fragment multiplicities. In the case of nontrivial partition weights the calculation of a bias function might be even more difficult than the calculation of a corresponding generating function.

Here, we propose a new method of the partition sampling which is designed especially for computer simulations. The idea is to generate a Markov chain by moving from one partition to another by minimal steps, i.e., by demanding that neighboring partitions differ by the state of one nucleon only. We shall refer to this method of generating partition samples as Markov Chain Generation (MCG). The procedure allows the following moves: (a) to transfer a nucleon from one fragment to another, (b) to make a nucleon free, or (c) to attach a free nucleon to a fragment. In addition, one must ensure that each new

partition is different from the previous one, since fragments with the same A are to be regarded as indistinguishable.

As well known, any sampling procedure of this kind must satisfy the detailed balance requirement. This can be achieved by applying the famous Metropolis algorithm [6], where a chain of partitions is generated by performing subsequent moves in the partition space biased by the partition probabilities W (weight factors). As shown elsewhere (e.g., ref. [7]), this method provides a correct description of the complete partition space for any specified weight factors W. In the MCG the number of all possible moves is limited and easily countable for any partition. By generating a new partition we account for the probability of all possible moves, and thus we avoid the bias function problem. Detailed balance is guaranteed by application of the Metropolis algorithm.

The numerical procedure is implemented in the following way:

Step I: For a given partition with M fragments of mass numbers A_i $(i = 1, ..., M)$, enumerate all fragments in the order of decreasing mass so that $A_1 \geq A_2 \geq ... \geq A_M$. This order is to be strictly maintained; any move violating this ordering is rejected. In this manner, we ensure that each move gives a genuinely new partition.

Step II: Select at random the fragment i that looses a nucleon and the fragment j $(j = 1, ..., M + 1; j \neq i)$ that accepts it. (The case $j = M + 1$ corresponds to making the nucleon free.) Check this move against the ordering requirement of Step I. If the order is violated, repeat the determination of i and j.

Step III: Calculate the weight of a new partition, W_{new}, and compare it with the weight of the previous one, W_{old}. A new partition is added to the ensemble if $W_{\text{new}} \geq W_{\text{old}}$. If $W_{\text{new}} < W_{\text{old}}$, a new partition is added with probability $W_{\text{new}}/W_{\text{old}}$. Otherwise, the old partition is taken as the new one and a new move is undertaken.

Step IV: Calculate the characteristics of interest by taking all partitions from the chain. The chain is truncated when these characteristics are saturated.

We stress that, contrary to the GF and BRG methods discussed above, the MCG method is a purely numerical procedure which requires nothing more than random number

generation. This provides a welcome degree of universality which is missing in other methods. For example, similar to the direct calculation, our method can be applied in case of any partition weight, as well as it can be easily generalized for other partition spaces, e.g., when fragments are characterized by two numbers (such as mass A and charge Z) instead of one [8].

The initialization problem, i.e., the question of which partition should be taken as a seed, does not appear to be important for the MCG method. The system with A_0=100 loses all memory of the initial partition after approximately 10^4 moves. In order to obtain a representative partition sample, one should just discard these initial partitions from the ensemble. This is verified for several cases when partition weights vary smoothly with fragment mass and the number of fragments. In other cases, the number of initial moves may increase. This problem must be analyzed in each particular case.

We have checked the MCG method in a number of ways. The results are presented in figs. 1-4 for two cases: first, when all partitions have equal weights (top panels) and second, when partitions with identical fragments are suppressed by the factorial weights $W_f = 1/\prod_A N_A!$ (bottom panels). They show the mean fragment multiplicity as a function of A (the mass distribution), the distribution of total fragment multiplicity, and a very specific characteristic, i.e., the distribution of multiplicities of particular fragments ($A = 1$, $A = 4$ and $A \geq 10$) taken over all partitions. The results of the exact direct method and of Markov chain generation are in remarkably good agreement. It should be stressed that for $A_0 = 100$ all 1.9×10^8 partitions are included in the direct method while only 10^5 partitions can be taken from the chain to explore the entire partition space with the MCG method. Small discrepancies in the tails of the distributions are seemingly related to a limited sample size and numerical precision. However they are not important in practice because of their very small relative weight in the chain. For smaller systems (e.g. A_0=20) the agreement is also good. For larger systems (e.g., A_0=1000), where the direct method is intractable, comparisons were made with the analytical GF method. As demonstrated in fig. 4, the agreement is quite good, apart of a small discrepancy in the

tails. One should bear in mind, however, that the GF method slightly overestimates the exact result (see fig. 1). We emphasize that the same high quality agreement between the direct and MCG methods is achieved in both considered cases which differ significantly by the weight factors. Calculations have been made for partitioning with other weights, and similar agreement has been found. Therefore, we believe that the MCG method described here offers a simple and correct numerical solution to the partition sampling problem.

In conclusion, we have analyzed several methods for calculating characteristics of the partition space of a finite composite system. We have developed a new numerical method, the Markov Chain Generation, which is flexible and efficient in practical calculations with complicated partition weights. We see a variety of applications of this method in different fields dealing with finite-size objects, from atomic nuclei to molecular clusters and astrophysical objects. We believe that this method will be very useful for studying the thermodynamics of finite systems [2, 3, 5, 8].

References

[1] G.E. Andrews, The Theory of Partitions, Vol. 2 in Encyclopedia of Mathematics and its Applications, ed. Gian-Carlo Rota, Addison-Wesley Publishing Co., Massachusetts, 1976.

[2] J.P. Bondorf, A.S. Botvina, A.S. Iljinov, I.N. Mishustin and K. Sneppen, Phys. Rep. **257**,133 (1995).

[3] S. Pratt and S. Das Gupta, nucl-th/9903006.

[4] J.P. Bondorf, R. Donangelo, I.N. Mishustin, C.J. Pethick and K. Sneppen, Phys. Lett. **250**, 57 (1985) *and* Nucl. Phys. **A443**, 321 (1985).

[5] D.H.E. Gross, Rep. Progr. Phys. **53**,605 (1990).

[6] N. Metropolis et al., J. Chem. Phys.**21**,1087 (1953).

[7] K.L. Chung, Markov processes with stationary transition probability. Springer, Heidelberg, 1967.

[8] A.S. Botvina, I.N. Mishustin *et al.*, work in progress.

Figure captions

Fig. 1. Average multiplicities $\langle N_A \rangle$ of fragments with mass number A for the system with total mass $A_0 = 100$. Solid lines: direct calculation taking into account all partitions, dashed lines: numerical Markov chain generation of partitions, dot-dashed lines: analytical calculations by the generating function method, dotted lines: biased random generation. Top panel: for partitions with equal weights, bottom panel: for partitions with the factorial weights $1/\prod_A N_A!$.

Fig. 2. Distribution of total fragment multiplicity M for the system $A_0 = 100$. Notations are the same as in fig. 1.

Fig. 3. Multiplicity distributions of fragments with $A = 1$, $A = 4$ and $A \geq 10$ for the system $A_0 = 100$. Notations are the same as in fig. 1.

Fig. 4. Comparison of fragment mass distributions for $A_0 = 20$ and 1000 calculated by the analytical and Markov chain generation methods. Top and bottom panels show calculations for two different weighting factors as above.

$A_0=100$

partitions with
equal probability

all partitions
Markov chain
analytical
biased random

partitions with
factorial weights

$\langle N_A \rangle$, mean multiplicity

A, fragment mass number

$A_0=100$

partitions with equal probability

partitions with factorial weights

all partitions
Markov chain
biased random

P(M), probability of multiplicity

M, total multiplicity

Top panel:

$A_0 = 100$

partitions with equal probability

$A \geq 10$

$A = 4$

$A = 1$

Bottom panel:

partitions with factorial weights

$A \geq 10$

$A = 1$

$A = 4$

all partitions
Markov chain
analytical

Vertical axis: $P(N_A)$, probability of multiplicity

Horizontal axis: N_A, fragment multiplicity

$A_0 = 1000$

$A_0 = 20$

partitions with equal probability

$\langle N_A \rangle$, mean multiplicity

partitions with factorial weights

all partitions
Markov chain
analytical

A, fragment mass number